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ABSTRACT

Political communication researchers recently have emphasized conditional relationships as crucial to specifying and understanding the effects of the mass media. In many cases, however, researchers will not predict which variables will modify the form or existence of media effects. They therefore will not include measures of the conditional variables in research designs. The presence of heteroscedasticity, or unequal precision of prediction at different levels of an independent variable, suggests the likelihood of an overlooked conditional relationship. This paper examines the possibilities for the use of statistical tests of variation in mass communication research. Research situations that employ both discrete and continuous independent variables are covered, and the visual examination of scatterplots as an alternative to performing variability tests is examined. Problems with the variation tests available on commonly used computer packages is addressed. A number of recently developed, apparently dependable variability tests also are presented. A research example involving two-way, linear interactions is provided. Additional concerns with unequal variability are also discussed. Three figures and a four-page list of references are included. (Author/PN)

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Looking for Heteroscedasticity: A Means of Searching for Neglected Conditional Relationships in Political Communication Research

by

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Abstract

Political communication researchers recently have emphasized conditional relationships as crucial to specifying and understandi e effects of the mass media. In many cases, however, researchers will not predict which variables will modify the form or existance of media effects. They therefore will not include measures of the conditional variables in research designs. The presence of heteroscedasticity, or unequal precision of prediction at different levels of an independent variable, suggests the likelihood of an overlooked conditional relationship. This paper discusses statistical and visual ways of looking for heteroscedasticity in designs employing both fixed and sampled independent variables. It presents an example from actual research. It also discusses additional reasons researchers may want to be concerned with unequal variability.

Looking for Heteroscedasticity: A Means of Searching for Neglected Conditional Relationships in Political Communication Research

> Almost all the greatest discoveries in astronomy have resulted from the consideration of what we have elsewhere termed RESIDUAL PHENOMENA, of a quantitative or numerical kind, that is to say, of such portions of the numerical or quantitative results of obse vation as remain outstanding and unaccounted for after subducting and allowing for all that would result from the strict application of known principles. (Sir John F. W. Herschel, as quoted in Draper & Smith, 1981, p. 141)

> Perhaps the most important reason to identify and study heteroscedasticity is that it may provide the only available evidence of interacting variables. Existing computer programs can search data sets for evidence of simple interaction; however, a finding of heteroscedasticity can provide a rationale for suspecting interaction with variables <u>not</u> included in the data set. (Downs & Rocke, 1979, p. 826)

Researchers in most scientific fields are quite familiar with what statisticians call a simple interaction: a situation in which the effect of one factor upon another, or the association of

one variable with another, changes at different levels of a third factor. Pharmacists and medical doctors, for example, have long realized that some combinations of drugs have synergistic effects on patients. If taken together, alcohol and barbiturates cause a much greater level of intoxication in people than would result from the additive, independent effects of the two. As another example, sociologists have provided evidence that the relationship between people's attitudes and behavior changes as social situations vary (Acock & DeFleur, 1972).

Political-communication researchers also frequently study interactions. In recent years, they increasingly have theorized about conditional and contingent effects of the mass media (e.g., McCombs, 1981; McLeod & Becker, 1981). A conditional effect occurs when the impact of the mass media varies among different types of persons or situations (McLeod & Reeves, 1980). A contingent effect--a specific form of conditional relationship--exists when an effect occurs only for certain people or in some situations.

The knowledge-gap hypothesis, for example, (Tichenor, Donohue, & Olien, 1970) predicts a conditional relationship between the availability of information from the mass media and people's learning of that information. Persons of higher socioeconomic status (SES) are expected to learn information contained in the media more rapidly than are lower-SES people.

Such research offers the prospect of an empirical synthesis

of two opposing strands in research in the field (McLeod & Becker, 1981, p. 72): the hypodermic model of the post World War I era and the limited-effects model. The former posited uniformly powerful media effects (see DeFleur & Ball-Rokeach, 1975, for a discussion). The latter model (Lazarsfeld, Berelson, & Gaudet, 1948; Klapper, 1961) followed research evidence that the mass media typically do not have a powerful impact on the attitudes and behavior of their audiences.

Persons testing conditional hypotheses often attempt to specify situations in which the media exert important influences, in the absence of uniformly powerful effects. Methodologically this implies a search for interaction. Researchers are advised to go beyond experiments that explore only main or overall effects (e.g., one-way designs) and survey analyses that use regression equations containing only an additive combination of predictors. Instead, they can examine media effects within subgroups differentiated by third variables such as SES (e.g., McNelly & Molina, 1972) or by including interaction terms in data analyses (e.g., Miller & Reese, 1982). McLeod & Reeves (1980, pp. 19-24) provide numerous examples of the many forms that interactions may take. They also discuss the imprecise or incorrect inferences one may make based upon data analyses that ignore combined effects of variables.

In certain cases, a researcher may include in surveys or experiments measures of concepts that he or she expects to

interact with media stimuli in producing an effect. One then can test an interaction for statistical significance. In many cases, however, theorizing about conditional relationships still is in a state of relative infancy. Researchers often will not predict when or if conditional relationships may exist, and they will not include measures of the relevant third variables as part of their research designs.

In these situations we need a means of checking whether an independent variable is likely to combine with an unspecified factor to influence a dependent variable. Statistical tests for heteroscedasticity (lack of homogeneity of error variation) or visual examinations of the uniformity of error represent reasonable, although less than perfect, means of examining an assumption of no interaction. In many research situations, unequal variability in a dependent variable at different levels of an independent variable indicates the strong possibility of an interaction (Downs & Rocke, 1979).

Such a finding should represent a warning to exercise care in interpreting results. It also should suggest the desirability of collecting additional data to try to find out with which factor an independent variable is interacting. In the present paper the possibilities for the use of statistical tests of variation in mass communication research will be examined. Research situations that employ both discrete and continuous independent variables are covered, and the visual examination of scatterplots as an

alternative to performing variability tests is examined. Problems with the variation tests available on commonly used computer packages will be addressed. A number of recently developed, apparently dependable variability tests also are presented, and a research example utilizing one of them is provided.

EXAMINING VARIATION: EXPERIMENTAL DESIGNS

In many cases, experimental researchers in mass communications associate tests on variances and variability with an assumption required by many inferential data-analytic techniques. Many of the most-common statistical tests for differences between or among group means--for example, Student's t and the F test--assume that within-group population variances are equal for all groups included in a study. A finding that group variances appear heterogeneous can mean that researchers lose some degrees of freedom in their tests and therefore need larger sample sizes to attain the same power. Generally, most researchers probably ignore variation tests entirely, in large part because standard experimental-design and statistics texts (e.g., Winer, 1971; Kirk, 1982) stress the robustness of the t and F tests to violations of the equal-variance assumption.

A few researchers in fields such as psychology, however, have understood that unequal variation may contain interest even without different group measures of central tendency. For

example, a study showed that performance in a concept-learning experiment was less variable with a human experimenter than when a computer served as the experimenter. This occurred in part because the human experimenter provided inadvertent task-related cues that aided low-ability subjects more than high-ability subjects (Johnson & Baker, 1973). In effect, the type of experimenter interacted with the ability of subjects to influence the outcome.

One hypothetical example from mass-communication research may help illustrate the point. Figure 1 depicts a case in which researchers have manipulated experimentally a factor that has equal and opposite effects for men and women on some important criterion variable (such a relationship might have emerged last fall if one had exposed men and women to Reagan campaign material and then questioned subjects' attitudes toward the president). Assume that the subjects included approximately equal numbers of each sex. If the experimenter did not utilize gender as an experimental variable, a test on group means would show no differences between treatment and control subjects. If variances about the means within each combination of sex and treatment or control group are equal, the subjects in the treatment group will exhibit greater variation than control subjects. Of course, had the researchers collected data regarding subjects' gender, they could easily test the interaction directly. If they failed to collect these data, however, unequal variation would represent the

only evidence of the interaction. Caution in concluding that the experimental treatment had no affect on people also would be advisable.

Figure 1 About Here

A common belief that available tests of variability are untrustworthy represents one possible obstacle to the acceptance of such methods in checking an assumption of no interaction. The most common test of the equality of group variability unfortunately is among the least reliable of all commonly encountered statistical methods. A researcher constructs this test statistic by taking the ratio of one group variance to another. The ratio then is compared with a critical value found in an F table with degrees of freedom equal to one fewer than the number of subjects in the first group and one fewer than the number of subjects in the second group. Like many other statistics, this requires an assumption that samples are drawn from normally distributed populations. Unlike what is commonly thought about most tests, however, the Central Limit Theorem does not allow a researcher using this particular F test to relax the assumption with moderate or large sample sizes (Hays, 1973). This test cannot be relied on with populations a researcher knows to be non-normal or with unknown populations.

Statisticians have developed and explored a number of alternatives to this F test and its generalization to research involving more than two groups, Hartley's F_{max}. Unfortunately, the alternatives most commonly encountered on standard computer packages--Bartlett's chi-square and Cochran's C--are similarly nonrobust to lack of normality (O'Brien, 1981). The Levene test (Levene, 1960) available on BMDP also seems to have the same problem (Brown & Forsythe, 1974).

Apparently trustworthy tests, however, are available to an industrious researcher, and some are quite easy to use. Following a critical synthesis of findings concerning the robustness of variance homogeneity tests, one methodologist (Keppel, 1982) recommended use of the Box test (Box, 1953) when evidence of asymetrical populations exists. The Box test involves dividing subjects within an experimental cell into small groups and calculating sample variances for each small group. A researcher then applies a logarithmic transformation to these variances, which become the observations for an Anova-type analysis (see Winer, 1971, pp. 219-220 for a clear explication of this procedure). Another statistician recently has developed a much-simpler alternative to this procedure (O'Brien, 1981). The W50 test, in which the dependent variable consists of the absolute deviations from cell medians, also seems robust to population non-normality (Brown & Forsythe, 1974).

One possible alternative to testing for inequality of

variances is a visual examination of a scatterplot such as Figure 1. One picture, some might argue, is worth a thousand test statistics. In many situations one can easily detect heteroscedasticity visually, and researchers always should examine these plots. In some cases, however, unequal error variation will not be visually evident, because the eye tends to look only for unequal ranges. In other instances, sampling error can produce what appears to be heteroscedasticity. Statistical tests allow a researcher to conclude formally whether an assumption of equal variation appears plausible.

EXAMINING VARIATION: SURVEY RESEARCH

Many survey researchers in communications, who often use simple- and multiple-regression techniques, are aware of the homogeneity of variance assumption. Most, however, probably ignore the assumption entirely. Others, upon detecting evidence of heteroscedasticity in a scatterplot, follow common advice (e.g., Draper & Smith, 1981) to transform the dependent variable to attain an apparent equality of variation. A few may use complex weighted least-squares techniques. Such practices reflect a common attitude that regression analysis exists to find average or predicted values of a dependent variable, and unequal variation merely represents a nuisance interfering with this aim (Downs & Rocke, 1979). Few appear to realize that heteroscedasticity can

suggest an incorrectly specified model.

Unfortunately, survey researchers frequently will have trouble using tests created to examine heteroscedasticity in experimental designs, which contain discrete independent variables. Their predictor variables are usually sampled and not fixed by the researcher prior to the study, and they often do not have more than one observation at any one level of an independent variable or combination of variables (see Figure 2).

Figure 2 About Here

On the other hand, statisticians have developed tests that fit this situation. Goldfeld and Quandt (1965) suggested two of the best known of these statistics.[1] Their tests apply in situations in which a researcher wonders whether error variation increases or decreases as one moves from lower to higher levels of an independent variable. The first test, a modified version of the F test on variances discussed earlier, requires an assumption of error normality. The other, the nonparametric peak test, requires no such assumption. Glejser (1969) suggested another test, which involves use of the absolute values of residuals as a dependent variable. With regression analysis, a researcher then could explore whether any significant relationship existed between

one or more independent variables and the residuals. This test could apply in situations in which residuals appeared larger toward the central values of an independent variable and smaller toward large and small values, or vice versa. One could explore whether a quadratic relationship existed between the independent variable and the absolute value of residuals, for example.

A question can arise concerning whether heteroscedasticity with reference to a predicted dependent variable (a common means of plotting data in multiple regression), rather than relative to a single independent variable, can suggest a neglected interaction. The answer is yes. If the residuals from a multiple regression analysis are normally distributed with a constant variance, the distribution of the dependent variable given a single independent variable also is normal with a constant variance (Downs & Rocke, 1979, p. 827).

EXAMPLE

The following example illustrates the utility of a test of homogeneity of variance in an experimental design. The debate over a New International Information Order (Masmoudi, 1979), which has featured complaints by the developing nations that the Western press covers underdeveloped areas of the world in a sparse and biased manner, suggested the research question. Perry (1984) was interested in the inferences people form about foreign nations

from samples of information supplied by the news media. He predicted that sensational news articles would have more influence on the accuracy of people's images of developing countries than on their judgments about developed nations.

A news story describing a small group of people in Ecuador with extremely lengthy life spans was used to test the hypothesis that news stories would have a more-damaging impact on the accuracy of judgments people make about developing countries than on their inferences regarding developed nations. Perry also used a simple random sample of 19 European and 19 African nations. The news story was typeset 38 times, with the name of each country substituted for Ecuador. Actual longevity figures mentioned in the articles were altered for the various countries so that each figure was, as much as possible, the same degree greater than the actual life expectancy for residents of each country.

The experimental subjects consisted of 76 students attending a state university during the summer of 1984. Perry asked the subjects to estimate the life expectancy of people in one of the 38 countries, to which they were assigned at random. Prior to making such an estimate, half the students read a news story concerning the country. Therefore, two students--one who had read a story and one who had not--estimated longevities of people in each country. Perry measured the accuracy of the inferences by taking the absolute difference, in years, between each participant's inference and the actual figure.

Responses were combined to form four experimental cells: African nation/no story, African nation/story, European nation/no story, and European nation/story. A planned comparison indicated support for the conditional or interaction hypothesis: the stories caused greater damage to the accuracy of inferences about African nations than to the accuracy of inferences concerning European countries, $t(72) = 3.26$, one-tailed $p < .05$. Overall, the stories had a large impact on the accuracy of African-country subjects; students who read a story missed actual life expectancies by an average of 47 years, and participants who read no story provided mean estimates that were only about 23 years off of actual longevity figures. It had much less influence on European-country participants; students who read a story missed actual figures by an average of about 17 years, only about four years more than the mean estimate of subjects not reading an article.

Suppose, however, that the researcher simply had wanted to study the impact of news stories on people's inferences about foreign nations, without regard to the geographic location of the countries. If he had not included the geographic location of the countries as an experimental variable in the design, he would have no means of testing for the conditional relationship. The researcher might wonder, however, whether subjects in general seemed uniformly influenced by the stories. One could explore this question by examining the overall effect of the story

treatments on the variability of people's estimates. A finding of statistical significance would suggest that the stories had a conditional effect on subjects—i.e., different effects on various persons with stimuli reflecting different countries.

This example utilized a transformation, r, suggested by O'Brieu (1981: 571) to achieve a robust test of variability. Individual dependent-variable observations within each of the two cells were transformed according to the following formula (written in terms of the $_j$th observation within the $_i$th experimental cell):

$$r_{ij} = (n_i - 1.5)\, n_i\, (y_{ij} - \bar{y}_i)^2 - 0.5\, s_i^{\,2}\, (n_i - 1)/(n_i - 1)\, (n_i - 2).$$

One first computes the mean and unbiased sample variance within each experimental cell. The researcher then squares the difference between the first observation and its cell mean. The square is multiplied times the product of the sample size within the cell and this sample size minus 1.5. From this figure one subtracts the product of three quantities: 0.5, the within-cell sample variance, and the within-cell sample size minus 1. The remainder then is divided by the product of the within-cell sample size minus 1 and this sample size minus 2. A researcher repeats the procedure for each observation within the experiment.

After completing this transformation, Perry applied a two-sample t test to the transformed scores. In other situations,

standard analyses of variance or planned comparisons could be employed.[2] The mean r values resulting were about 198 for the no-story subjects and 374 for the story subjects (with this transformation, the mean r value equals the original variance within the experimental cell). The t value for the difference between the two means was significant, $t(74) = 2.65$, two-tailed $p<.05$, indicating that the accuracy of inferences among subjects who read the story varied more than the inferential accuracy among no-story participants. Such a pattern of heteroscedasticity would be produced if the stories had a more powerfully damaging effect on some subjects than on others. Of course, in this case we know from actual research that the unequal variabilities reflected the conditional relationship produced by the geographical location of the countries mentioned in the stories.

As a final step, Perry regrouped the observations into the original four cells of the experiment. He then recomputed O'Brien's r, reflecting the four-cell design, for each observation. An overall F test for the four cells failed to attain significance, $F(3, 72) = 1.68$, $p>.05$, indicating that an assumption of homogeneity of variability--and an assumption of lack of additional interaction--n·· appears plausible.[3]

CONCLUSION

In this paper a case has been made for the use of tests for

heteroscedasticity in exploring whether a researcher has overlooked a conditional relationship. Readers should be warned, however, that conditions other than interacting variables can sometimes produce heteroscedasticity. Other forms of incorrect model specification can result in unequal variability (see Goldfeld & Quandt, 1965 for a discussion of one example). In addition, floor and ceiling effects in measurement can deflate variances (O'Brien, 1981), and variance tests occasionally have been used to test for the presence of these artifacts (e.g., Holzman, Pellegrino, & Glaser, 1982).

There is, of course, no guarantee that a real, but overlooked, conditional relationship will produce significantly unequal variation. For one thing, the power of variation tests usually is lower than the power of tests concerning central tendency (Keppel, 1982, p. 99). In addition, Figure 3 illustrates one hypothetical, and probably rare, interaction pattern in an experimental design that would yield equal variances between a treatment and a control group. In this case, an interaction pattern is disordinal or transverse (the lines connecting the treatment and control groups, within subgroups, cross), and both variables are dichotomous. In addition, no main effect is present either for the treatment or the subgroup factor.

Figure 3 About Here

More generally, when a researcher utilizes dichotomous independent variables, ordinal interactions (in which lines do not cross within the utilized range of independent variables) will have a greater impact than will disordinal interactions on variability. Situations in which disordinal interactions have no impact on variation probably are not too common, however. For instance, if one independent variable is continuous and the other dichotomous, a disordinal interaction between them normally would expand variability among observations at extreme ends of the continuous variable, relative to observations toward the center.

This paper has used examples involving only two-way, linear interactions. Higher-order and nonlinear (e.g, quadratic) interactions also should influence variation in most cases, although very specific situations exist in which they may not.

In some cases, unequal variability may have theoretical import, beyond possibly suggesting the presence of a neglected interaction. For example, Jeffersonian political thought posits the desirability of multiple views on public issues and a diversity of public opinion. Chaffee and Wilson (1977) tested whether audience agendas in media-rich towns were more varied than public agendas in media-poor areas. Their dependent variable

attained only a nominal level of measurement, and Chaffee and Wilson utilized an information-theoretic measure of nominal diversity. Other researchers might explore whether people who read two or more newspapers exhibit more variation on conventional attitude measures than single-newspaper readers, for example. To do so, one could apply a variation measure such as O'Brien's r to data generated by a Likert-type scale, for instance.

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Footnotes

[1]As described in the 1965 article, the Goldfeld-Quandt tests apply to instances in which a researcher wonders whether a ratio, rather than linear, model fits a set of data. The tests would not be useful in situations described here if they only applied in that instance. They can be used in much more general situations, however (Goldfeld & Quandt, 1972, p. 85-91).

[2]O'Brien (1981, p. 572) warns researchers who perform contrasts on a subset of cells within an experiment against using a pooled estimate of the error term following the r transformation.

[3]It is crucial to remember that such tests do not eliminate the possibility that the treatments employed in an experiment actually yield unequal variation. All they indicate is whether an assumption of equal population variability remains credible.

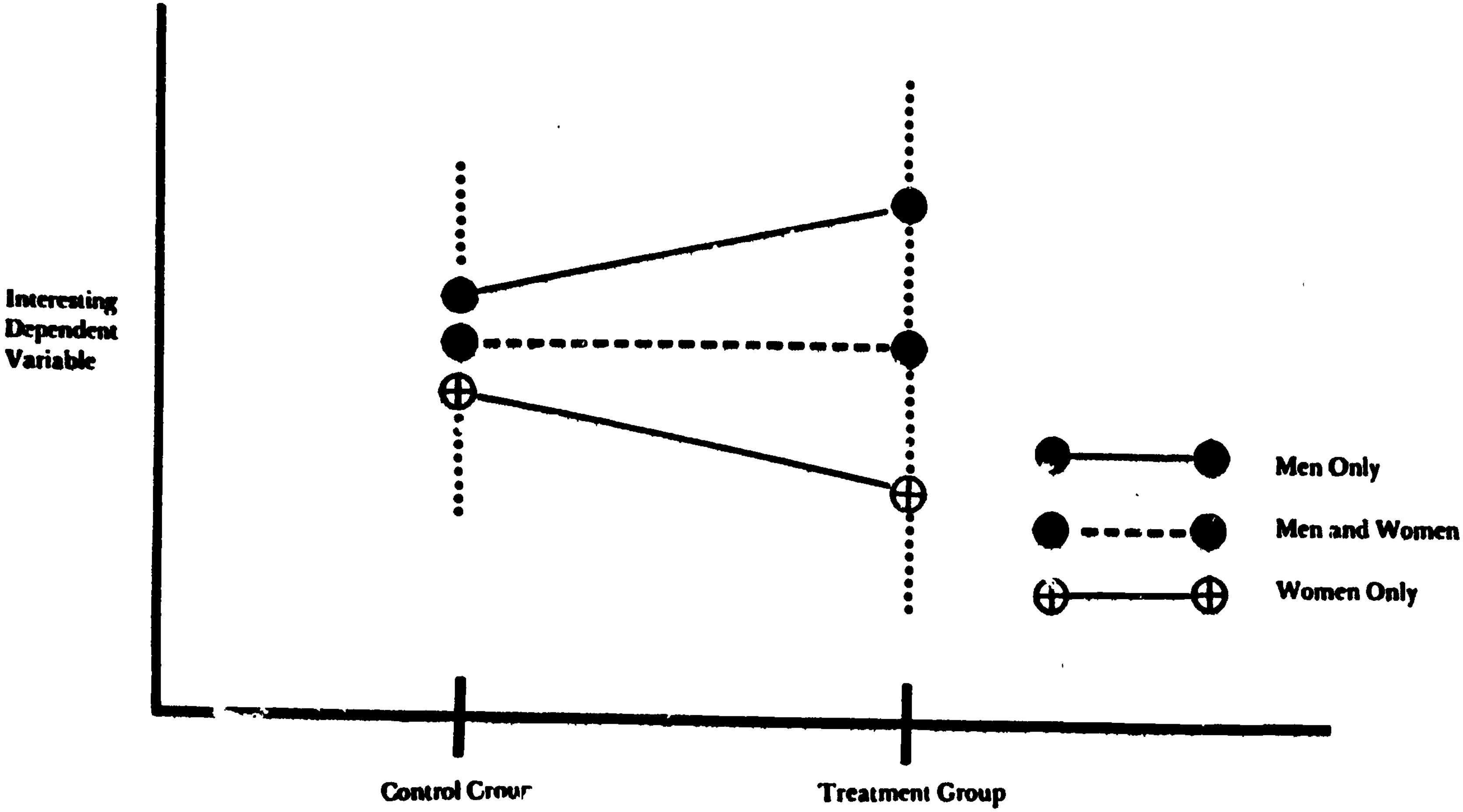

Figure 1. Hypothetical plot of heteroscedasticity in one-way experimental design, ignoring an interaction.

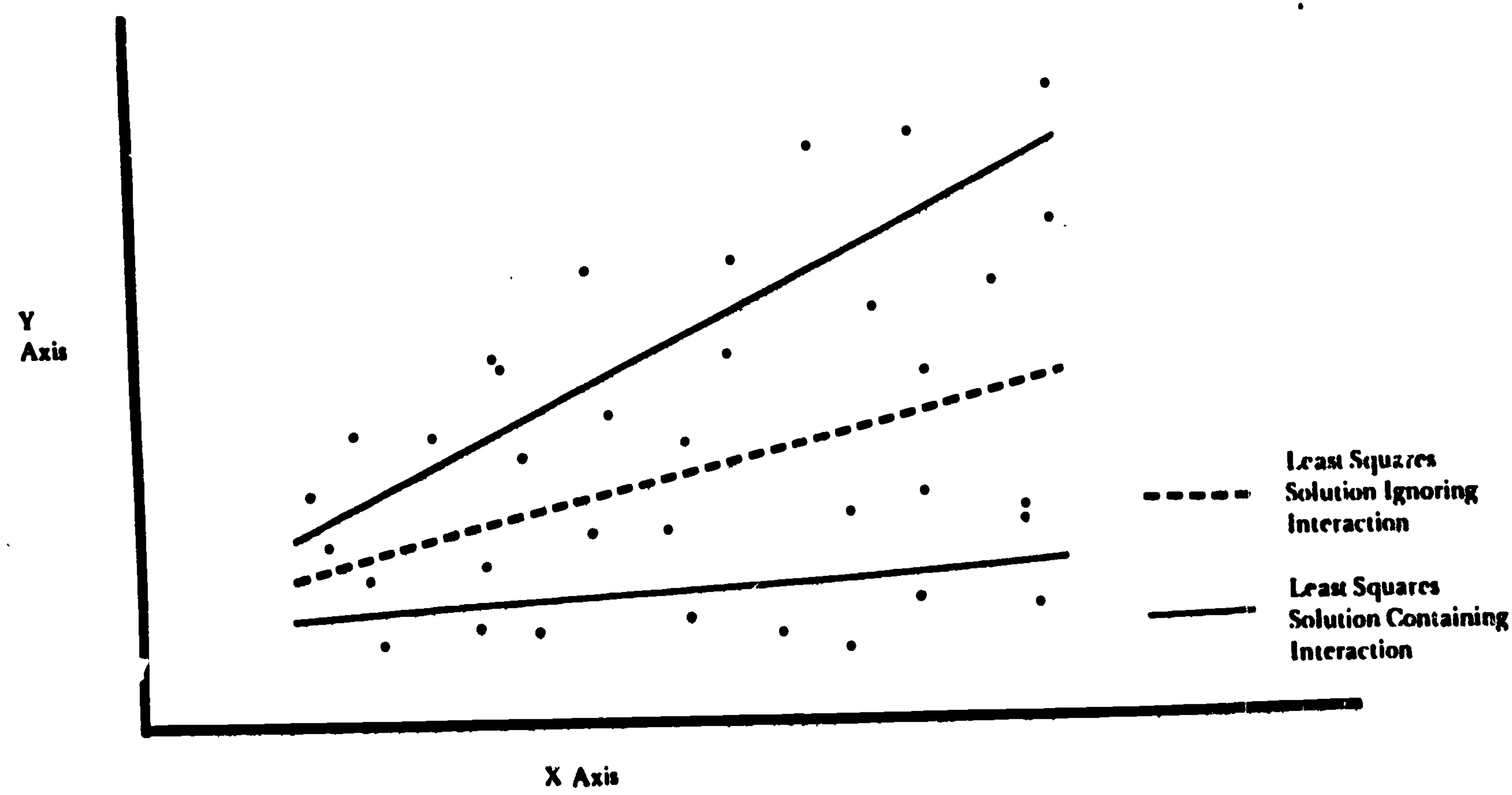

Figure 2. Hypothetical plot illustrating regression heteroscedasticity if an interaction involving a dichotomy is ignored.

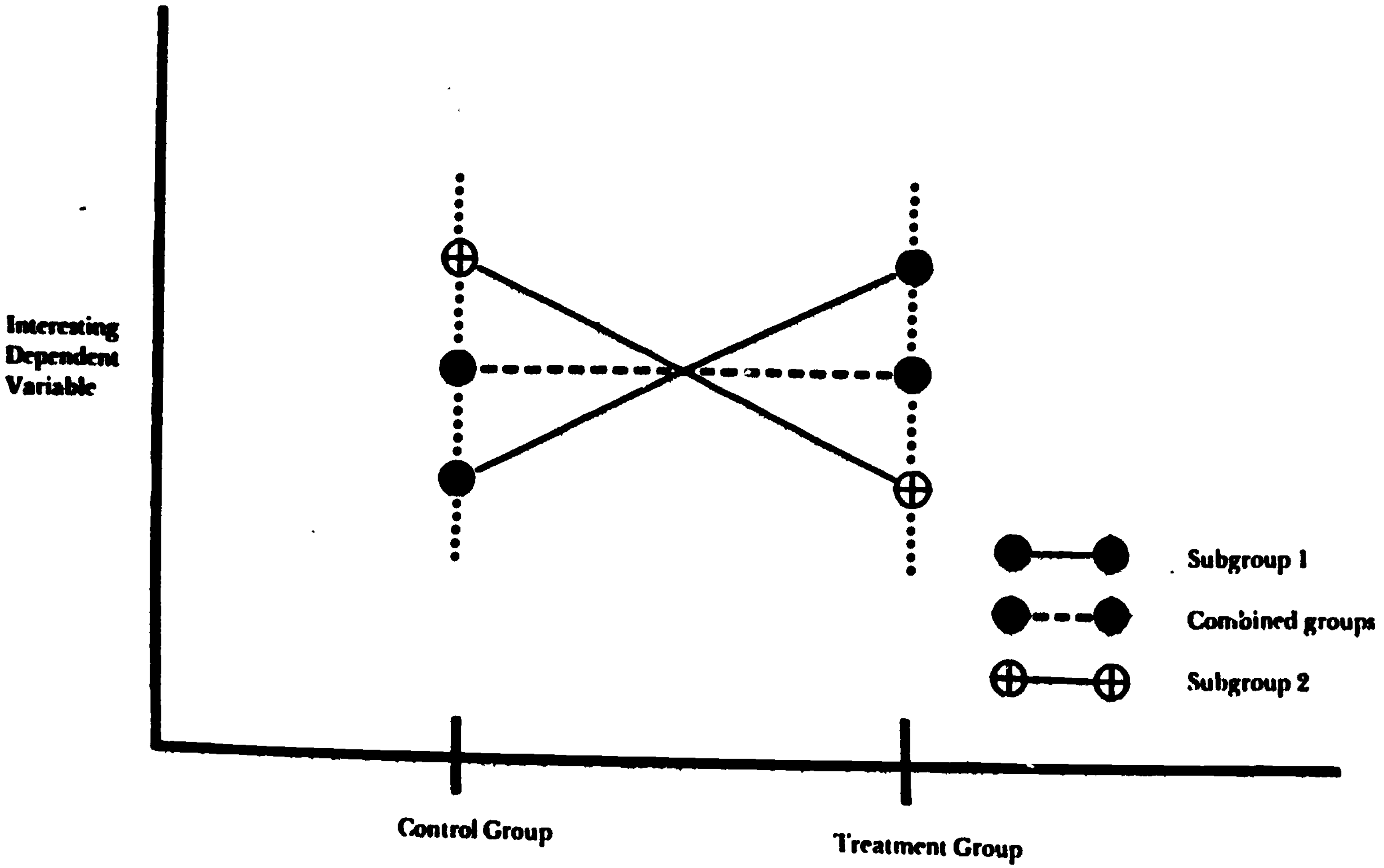

Figure 3. Hypothetical plot of homoscedasticity in an experimental design, regardless of whether an interaction is ignored.